Generative Adversarial Malware Classifier Deceptor with Reinforcement Learning

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Definitions

Generative Adversarial Malware Classifier Deceptor with Reinforcement Learning

Generate modified Malware that...

Can bypass a Malware Classification as Benign...

Through an unsupervised Machine learning method

Reinforcement Learning Fundamentals

Action Space: the full set of possible actions.

Agent: The thing that takes actions.

State: An agent’s immediate condition.

Environment: Takes in Agent and Agent’s state. Then, outputs an observation.

Episode: Steps which is how many times the model is updated from each taken action before the terminal state.

Observation: A reward and next Agent’s state.

Reward: Performance feedback from an instance of the environment.

Policy: How the agent decides the next action.

An action: rename_section

Environment: Mutating sample, vectorizing and testing against the classifier.

An Episode: Send (rename_section, a malicious sample) to environment. New score below threshold, environment returned a value of .80 which is below threshold .9.

Observation: Sample evaded, end episode, give big reward.

Reward: 10

State: Evaded.

Policy: Boltzmann Exploration Policy.

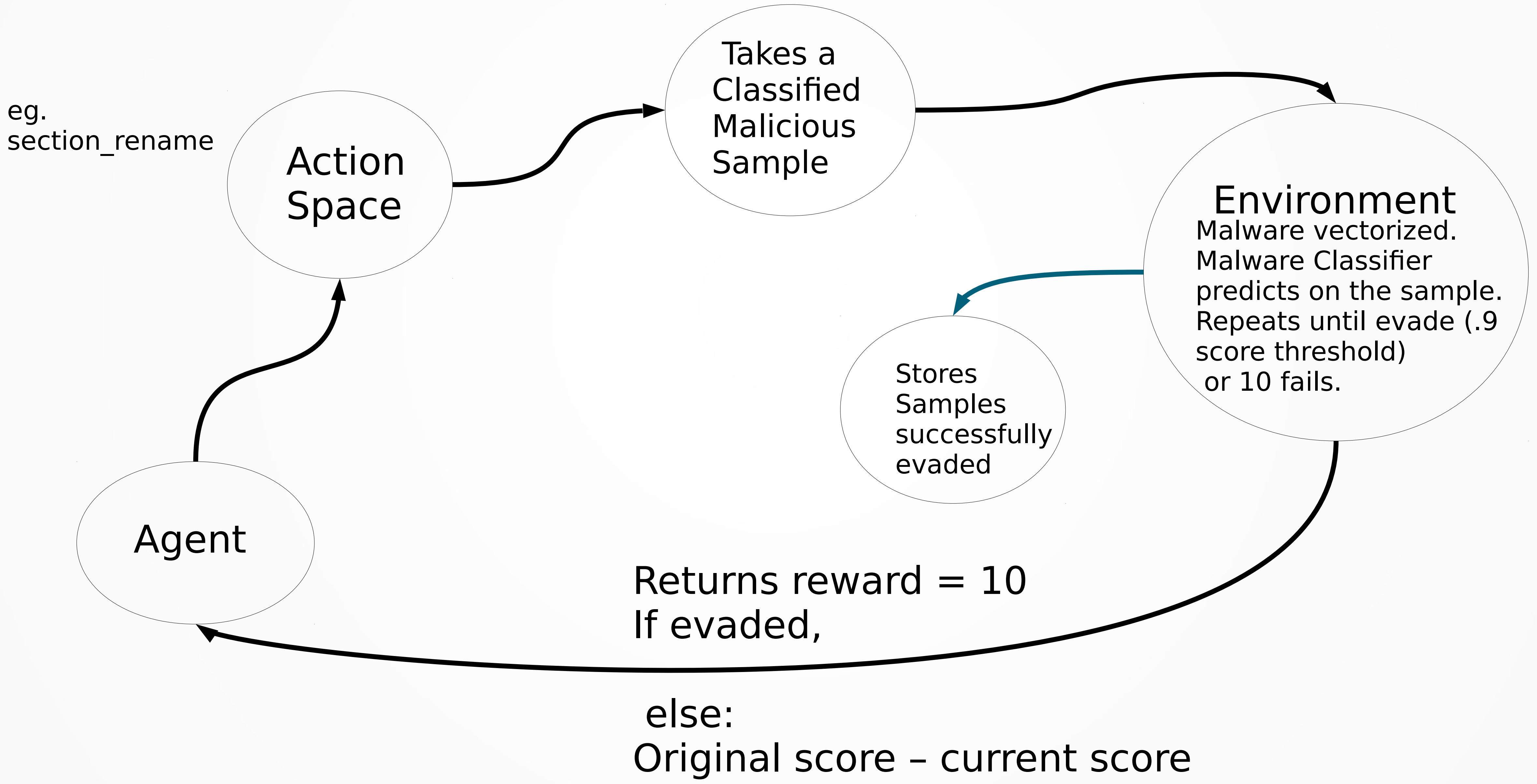
Reinforcement Learning Continued.

- Model-based
  - Markov Decision Process
  - All elements are known:
    - S → State
    - A → Set of Actions from Action Space
    - R(s,a) → The function that returns reward for action a.
    - T(s’ |s,a) → The transition probability function for environment transition to state s’ given state s and action a.
    - A model of the environment is made where probabilities of all states and transitional-state from all possible actions are calculated.
- Model-Free
  - Does not use the function T nor function R.
    - “Trial and Error”
    - No model of the environment, no prior knowledge and learns from experience.

RL continued. Again

- Temporal Difference (TD) Learning
  - Model-free method
  - Predictions are adjusted before final outcome unlike Monte Carlo methods.
- To calculate an optimal policy:
  - Q-Learning (Quality)
    - Method of finding an optimal policy that maximizes total reward (expected reward) over all steps up until current state. Uses Q-table which is a matrix that assigns pairs of actions with states with an overall expected reward value.
    - Off-policy – unlike on-policy, does not use its current policy to update Q-values.
      - Deep QL
        - Instead of a paired action-state Q-table, a neural network layer is used where the input layer is the states and the output layer is the actions.
      - Double DQL (Double Deep Q-Learning)
        - Q and Q’ are networks with identical architecture, To update Q(s,a), the action is selected from Q with maximum expected reward given state s, but Q’ is given the state and action to calculate the Q-value.

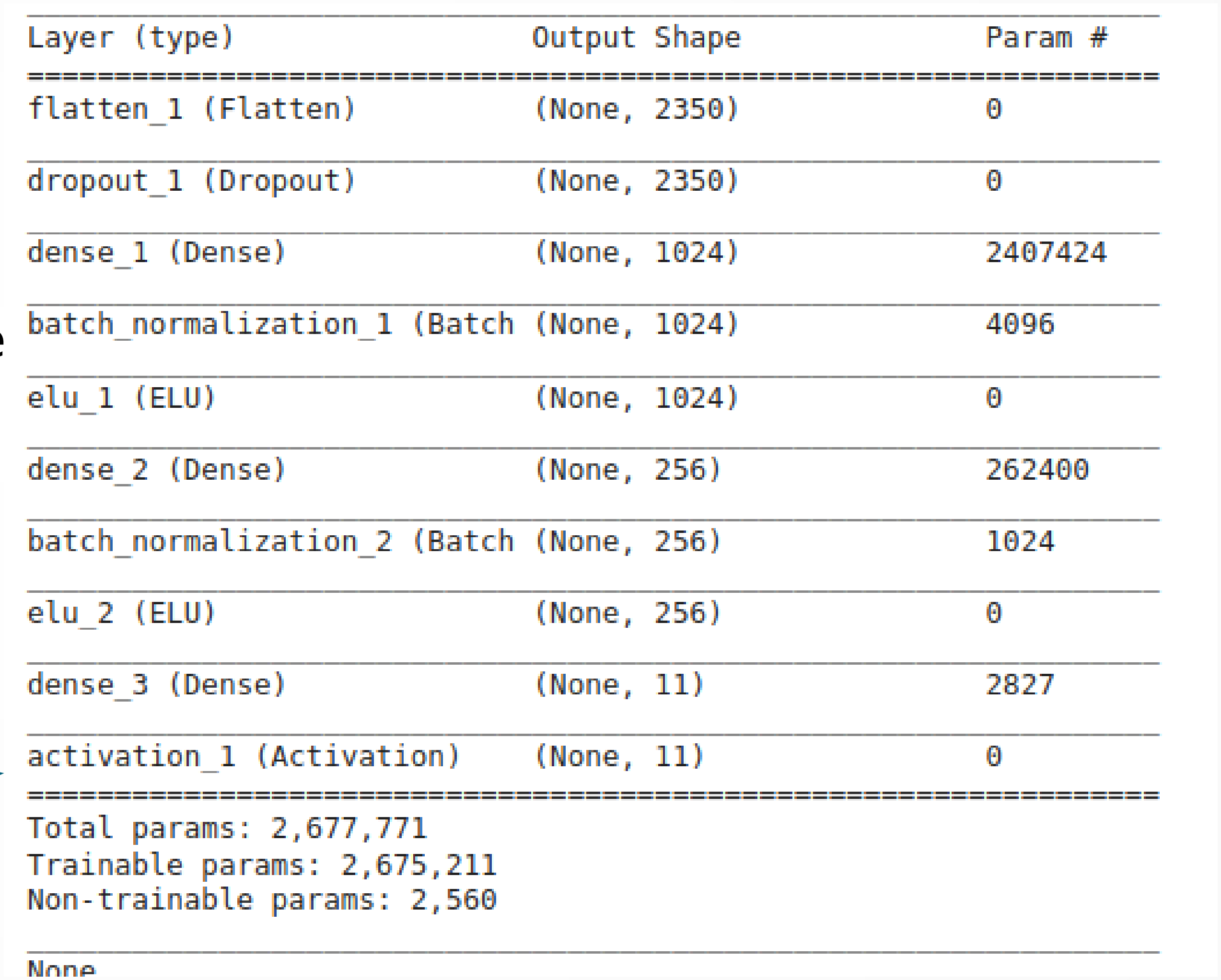
Generative Adversarial Malware Classifier Deceptor


eg.
section_rename
Action Space
Takes a Classified Malicious Sample
Environment
Malware vectorized.
Malware Classifier predicts on the sample.
Repeats until evade (.9 score threshold)
or 10 fails.
Stores Samples successfully evaded
Agent
Returns reward = 10
If evaded,
else:
Original score – current score

Model Architecture

- DQL Agent: Double DQL Architecture, making it off-policy.
- Policy: Boltzmann Exploration Policy – stochastic policy where an action is selected by a generated probability of the softmax expected rewards/Q-values.
- Memory : Each malware sample is an experience
- Optimizer: RMSProp
- Metric: mae
- Iterations = Number of Training samples (Episode) * 10,000 * 5
  = 1.5 days of training

Action space size



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
flatten_1 (Flatten)          (None, 2350)              0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 2350)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              2407424   
_________________________________________________________________
batch_normalization_1 (Batch (None, 1024)              4096      
_________________________________________________________________
elu_1 (ELU)                  (None, 1024)              0         
_________________________________________________________________
dense_2 (Dense)              (None, 256)               262400    
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024      
_________________________________________________________________
elu_2 (ELU)                  (None, 256)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 11)                2827      
_________________________________________________________________
activation_1 (Activation)    (None, 11)                0         
=================================================================
Total params: 2,677,771
Trainable params: 2,675,211
Non-trainable params: 2,560
_________________________________________________________________
None
```

Before the Results

- Boltzmann Q Exploration Policy makes it a stochastic model. The results can vary.
- The random selection for Benign section names is also a distribution that can contribute to variation in results.
- The Malware Classifier is a Gradient Boost Decision Trees Model

- The original dataset size was 14. The test split is set to .2-- which allows up to 2 samples in test set. However, only one sample classified as Malicious from the Malware Classifier. Only 5 out of the 14 samples were classified as Malicious from the Classifier.

Ransomwares

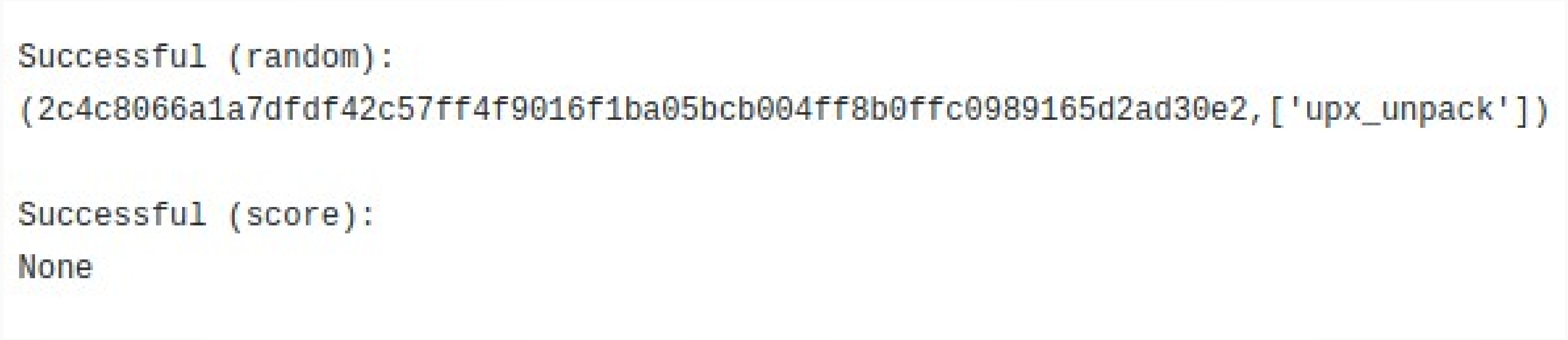
Classified as Benign

Able to Evade with policy.

- ('Ransomware.Satana_sha256', '683a09da219918258c58a7f61f7dc4161a3a7a377cf82a31b840baabfb9a4a96')
- ('Ransomware.Petrwrap_sha256', 'd975bc89371be98a80f9979e4a3c517590029e61ff36605b48b883c723024bde')
- ('Ransomware.Petrwrap_sha256', '4340f4c633a53d45de440293d1f09f839467cc4734f499b466e9c58ee7493020')
- ('Ransomware.Petrwrap_sha256', '3419e0d470f83569be0927128b3e5f992800ceb8f9019fc44763876ed6d8000c')
- ('Ransomware.Petrwrap_sha256', '027cc450ef5f8c5f653329641ec1fed91f694e0d229928963b30f6b0d7d3a745')
- ('Ransomware.Petrwrap_sha256', 'e5c643f1d8ecc0fd739d0bbe4a1c6c7de2601d86ab0fff74fd89c40908654be5')
- ('Ransomware.Radamant_sha256', '2c4c8066a1a7dfdf42c57ff4f9016f1ba05bcb004ff8b0ffc0989165d2ad30e2')
- ('Ransomware.Petya_sha256', '4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea45308b8c49b950655c')
- ('Ransomware.Petya_sha256', '26b4699a7b9eeb16e76305d843d4ab05e94d43f3201436927e13b3ebafa90739')
- ('Ransomware.Unnamed_0_shasum', '517ac5506a5488a1193686f66cb57ad3288c2258c510004edb2f361b674526cc')
- ('Ransomware.Cryptowall_sha256', '45317968759d3e37282ceb75149f627d648534c5b4685f6da3966d8f6fca662d')
- ('Ransomware.Cerber_sha256', 'e67834d1e8b38ec5864cfa101b140aeaba8f1900a6e269e6a94c90fcbfe56678')
- ('Ransomware.Mamba_sha256', '2ecc525177ed52c74ddaaacd47ad513450e85c01f2616bf179be5b576164bf63')
- ('Ransomware.WannaCry_sha256', 'ed01ebfbc9eb5bbea545af4d01bf5f1071661840480439c6e5babe8e080e41aa')

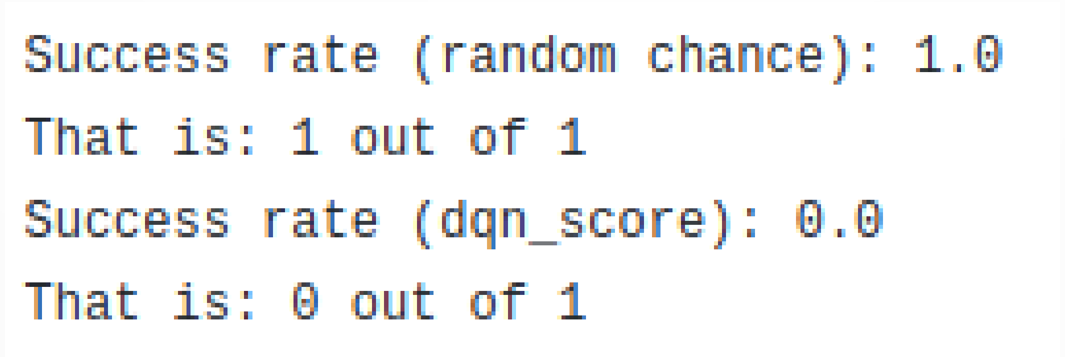
Evaded Randomly

Results on Test Set



```
Successful (random):
(2c4c8066a1a7dfdf42c57ff4f9016f1ba05bcb004ff8b0ffc0989165d2ad30e2,['upx_unpack'])

Successful (score):
None
```

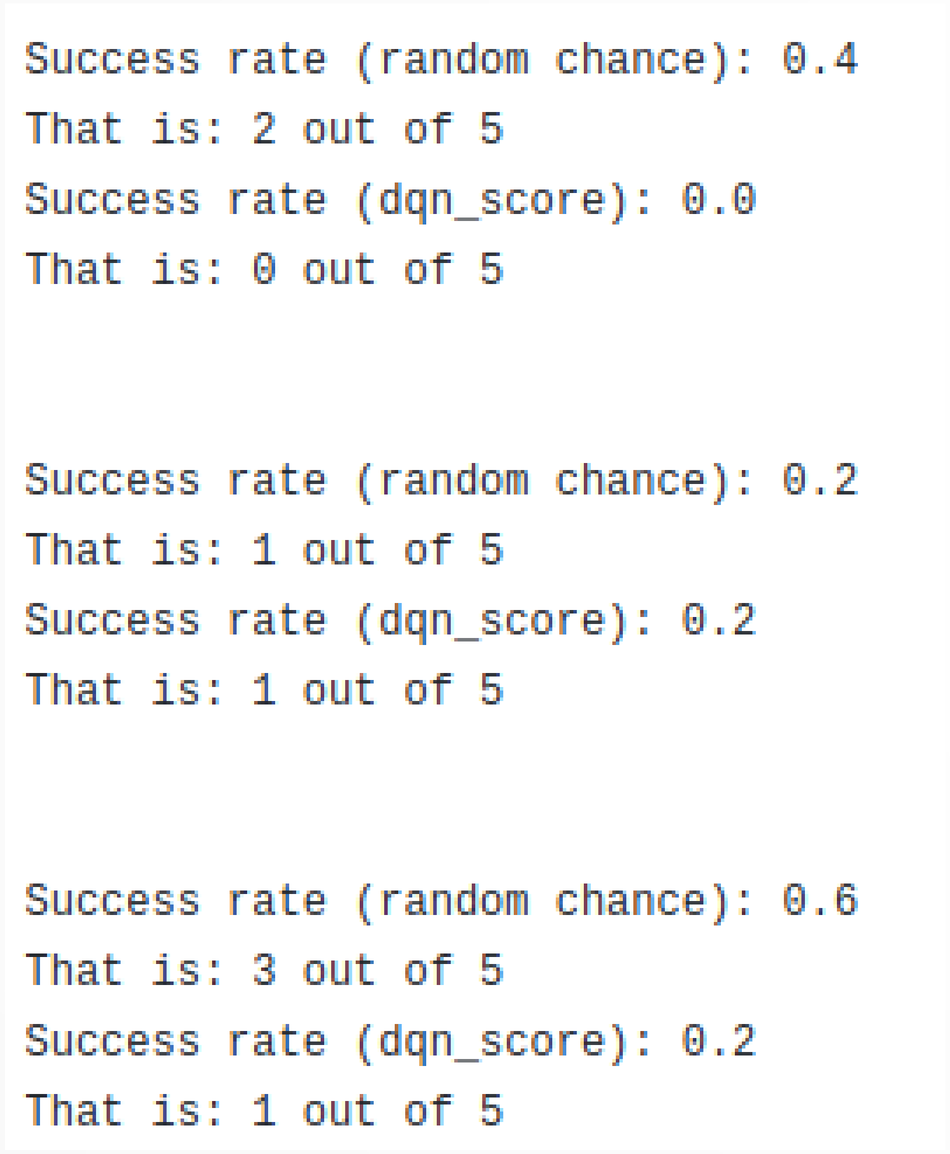
6x iterated on the test set. This was the generic output.



```
Success rate (random chance): 1.0
That is: 1 out of 1
Success rate (dqn_score): 0.0
That is: 0 out of 1
```

Though, the first model was able to have some instances correct, after training the model more, it moved away from that local minimum.

Result on Full Set



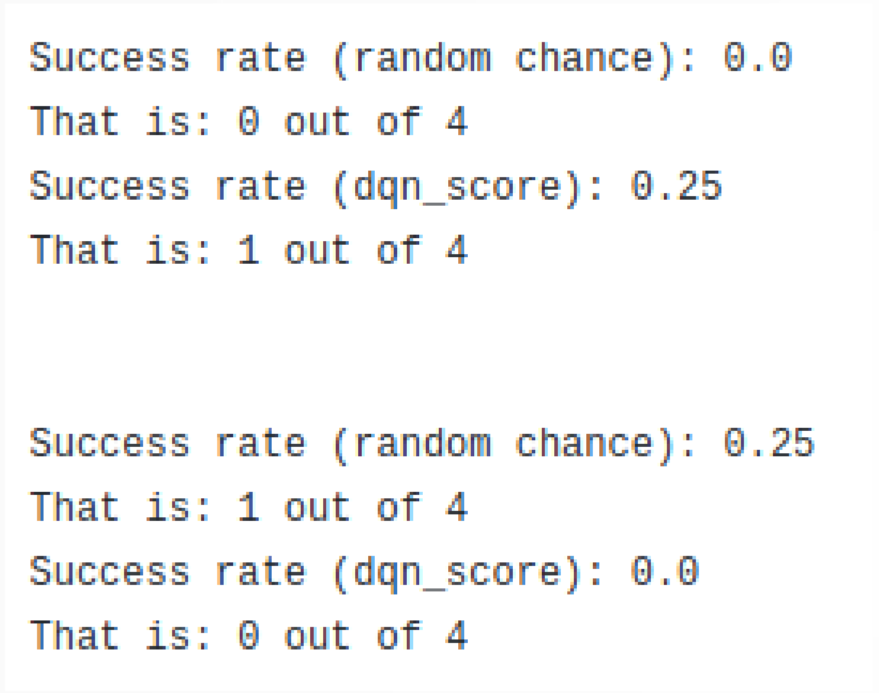
```
Success rate (random chance): 0.4
That is: 2 out of 5
Success rate (dqn_score): 0.0
That is: 0 out of 5


Success rate (random chance): 0.2
That is: 1 out of 5
Success rate (dqn_score): 0.2
That is: 1 out of 5


Success rate (random chance): 0.6
That is: 3 out of 5
Success rate (dqn_score): 0.2
That is: 1 out of 5
```

Successful (score):
None

Successful (score):
(e5c643f1d8ecc0fd739d0bbe4a1c6c7de2601d86ab0fff7
4fd89c40908654be5,['section_rename'])

Successful (score):
(517ac5506a5488a1193686f66cb57ad3288c2258c5100
04edb2f361b674526cc,['section_rename',
'section_rename', 'section_rename', 'section_rename',
'section_rename', 'section_rename', 'section_rename',
'section_rename', 'section_rename'])

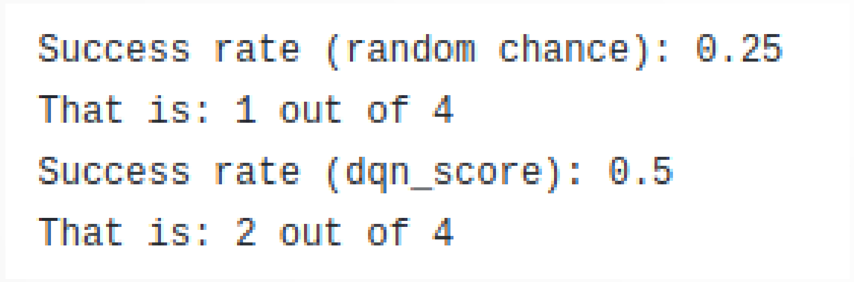
Results on Train



```
Success rate (random chance): 0.0
That is: 0 out of 4
Success rate (dqn_score): 0.25
That is: 1 out of 4


Success rate (random chance): 0.25
That is: 1 out of 4
Success rate (dqn_score): 0.0
That is: 0 out of 4
```

Successful (score):
(517ac5506a5488a1193686f66cb57ad3288c2258c51000 4edb2f361b674526cc,['section_rename', 'section_rename', 'section_rename', 'section_rename', 'section_rename', 'section_rename', 'section_rename', 'section_rename'])

Successful (score):
None



```
Success rate (random chance): 0.25
That is: 1 out of 4
Success rate (dqn_score): 0.5
That is: 2 out of 4
```

Successful (score):
(4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea4530 8b8c49b950655c,['section_rename', 'section_rename', 'section_rename', 'section_rename', 'section_rename'])
(e5c643f1d8ecc0fd739d0bbe4a1c6c7de2601d86ab0fff74fd89 c40908654be5,['section_rename'])

Model Learned or Luck?

rename_section

PRO

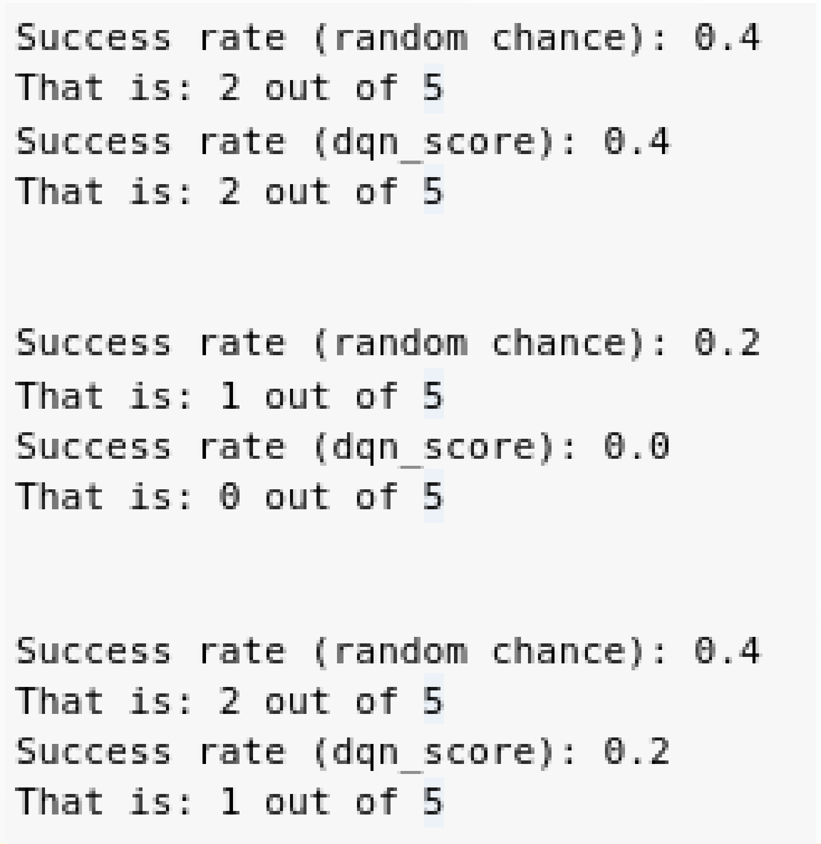
Repeated across the subsets.
Same samples evaded with same actions.
During testing, action repeated despite failing.
Random chance on name selection could be part of the reason of its inconsistency.
Original paper results also supports.

Con

Is still a probabilistic model.
Simple evasions were done by the random choice model consistently… why wasn’t it learned.

What can be done?

- It was trained on a stochastic policy, would a deterministic policy provide different test results? Let’s see… On full set



```
Success rate (random chance): 0.4
That is: 2 out of 5
Success rate (dqn_score): 0.4
That is: 2 out of 5


Success rate (random chance): 0.2
That is: 1 out of 5
Success rate (dqn_score): 0.0
That is: 0 out of 5


Success rate (random chance): 0.4
That is: 2 out of 5
Success rate (dqn_score): 0.2
That is: 1 out of 5
```

Successful (score):
(e5c643f1d8ecc0fd739d0bbe4a1c6c7de2601d86ab0fff74fd89c40908654be5,['section_rename', 'section_rename', 'section_rename', 'section_rename'])
(4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea45308b8c49b950655c,['section_rename'])

Successful (score):
None

Successful (score):
(4c1dc737915d76b7ce579abddaba74ead6fdb5b519a1ea45308b8c49b950655c,['section_rename', 'section_rename', 'section_rename', 'section_rename'])

Wasn’t great results but was helpful.

- It wasn’t entirely random… since the best action selection resulted in the same set of samples across all testing to evade with similar actions as the Boltzmann Q Policy.
- The model did learn something…
- The inconsistency between the number of same actions for the same samples strongly suggests that the probability distribution in the action space: eg. selecting a benign section name from existing names affects the Malware’s ability to evade.

Things I’d change (Again)

- Change the action space, separate any actions that randomly select a benign feature from a pool into separate actions.

  Eg. “rename_section” would be partitioned into actions: “rename_section_benign1”,”rename_section_benign2”….etc. This will allow the policy to select the best action in rename_section and create its own probability distribution for the actions.

Takeaways/Future Ideas

- Was able to create 953 modified Ransomwares from at most 5 samples with unique sha256 signatures.
- An ensemble of models where their generated samples are unioned, say the random select model and the trained model, then tested against the Classifier will result in this particular selection of Ransomware, 100% of the classified malicious samples being capable of fooling the Classifier.
- Take the model and turn it into a generator for a Malware Classifier to use to train on for data augmentation.

Execute the Project!

- Samples can be taken from:

  https://github.com/ytisf/theZoo
- Jupyter Notebook For Acquiring Samples:
- https://drive.google.com/open?id=1sQ6rTBX0by2NANehxM50SH3rcU1FJdSE
- Jupyter Notebook to Train a Model:

  https://colab.research.google.com/drive/1I-dXUroohAwgfmHiJq03ylLvC-DHnu8N
- Remember if you plan to resume training at a later date and store it on Google Drive, to encrypt the compressed folder.

Citations

- Hyrum S. Anderson, Anant Kharkar, Bobby Filar, David Evans, Phil Roth, "Learning to Evade Static PE Machine Learning Malware Models via Reinforcement Learning", in ArXiv e-prints. Jan. 2018.